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A multiple traveling salesman problem model for hot rolling scheduling in Shanghai Baoshan Iron & Steel Complex ☆

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Abstract

This paper presents the model, solution method, and system developed and implemented for hot rolling production scheduling. The project is part of a large-scale effort to upgrade production and operations management systems of major iron and steel companies in China. Hot rolling production involves sequence dependent setup costs. Traditionally the production is scheduled using a greedy serial method and the setup cost is very high. In this study we propose a parallel strategy to model the scheduling problem and solve it using a new modified genetic algorithm (MGA). Combing the model and man–machine interactive method, a scheduling system is developed. The result of one year's running in Shanghai Baoshan Iron & Steel Complex shows 20% improvement over the previous manual based system. As the company is one of the largest steel companies and the most modernized one in China, the successful application of the scheduling system in this company sets an example for other steel companies which have more potentials for improvement. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Iron and steel industry; Hot rolling production; Scheduling; Multiple traveling salesman problem; Genetic algorithms (GAs)

1. Introduction

Iron and steel industry is essential for any industrial economy, providing the most important materials for other industries. It also often serves as a driving force for the whole industrial development. This is especially the case for rapidly developing economies. An example in the 1970s and 1980s was South Korea which had rapid development of its steel industry during the period and became one of the newly industrialized countries. For the last 20 years, China has been leading the world in steel production growth with a remarkable speed. Its steel production increased quickly from 37 million tons in 1980 to 61 million tons in

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1989. By then, researchers still doubted that an adjusted target of 90 million tons by the year 2000 could be reached [1]. However, when its production reached 81 million tons in 1992, it was believed that the original goal of 100 million tons by the year 2000 was readily obtainable [2]. In 1996, its production already reached 100 million tons [3], four years ahead of the plan. Such a rapid growth in steel production has provided strong support for its massive construction projects and high-speed growth of its manufacturing industries. In recent years, other developing countries such as India and Brazil have also set ambitious goals for their steel industries as an important part of their economic development plans.

On the other hand, steel industry is capital and energy intensive while developing countries often face shortages of these resources. Therefore, at the same time of increasing steel production capacities, it is critical for these countries to best utilize their existing capacities. One important way to achieve this is through effective production scheduling. The benefits of using an effective scheduling method include considerable improvement in production efficiency and product quality, and great reduction in production cost. In this paper we present the model, solution method, and system developed and implemented for hot rolling production scheduling in Shanghai Baoshan Iron & Steel Complex.

In iron and steel industry, the hot strip mill is often considered the bottleneck of the overall production process. Production sequencing of steel orders through the hot rolling mill is the key to the hot strip mill production scheduling. To ensure product quality, smooth thickness or gauge transitions from order to order and a gradual width decreasing pattern are necessary in the rolling process. Setup is required for dramatic transitions. The continuous production between two setups is called a turn. Scheduling the orders on the hot strip rolling mill for a production shift is to form the production turns and arrange the sequence for rolling the individual orders in each turn, considering the constraints of the mill. The objective is to minimize transition (setup) cost in the production sequence. Traditionally the problem is solved through sequentially arranging each turn by selecting orders from those unscheduled. This is a greedy method considering only local optimum for one turn at a time. It normally results in large setup costs for later arranged turns.

To achieve more effective hot roll production and reduce setup cost, we propose a parallel strategy in this paper to simultaneously schedule multiple turns for the whole shift from a global optimal view. Using the proposed parallel strategy, the hot rolling scheduling problem is modeled as a multiple traveling salesman problem (MTSP) based on actual production constraints. To solve the problem, the MTSP model is then converted into a single traveling salesman problem (TSP) model. A modified genetic algorithm (MGA) is constructed to obtain a near-optimal solution to the TSP. A new selection rule is introduced to the crossover operation (seed based crossover) in the MGA framework. Combining the proposed MTSP model and the MGA procedure with man–machine interactive method, a practical hot rolling scheduling system is developed and implemented in Shanghai Baoshan Iron & Steel Complex.

The rest of this paper is organized as follows. Previous related work and the current status of hot strip rolling mill scheduling research are first reviewed in Section 2. Section 3 describes the hot strip rolling production process and scheduling constraints. The parallel modeling strategy and its advantages over the serial one are presented in Section 4. In Section 5, the MTSP model for rolling scheduling using the parallel strategy is established. The MGA applied to hot rolling scheduling is presented in Section 6. Section 7 reports computer experiments using actual production data and the implementation of the hot rolling scheduling system. Section 8 gives the conclusions.

2. Literature review

Solving production operational management problems in steel rolling mills is an important research topic and has been widely explored recently. At present, research on hot rolling scheduling mainly adopts the following three types of methods: (1) operations research methods, (2) artificial intelligence (AI) methods, and (3) human–machine coordination methods.

2.1. Operations research based methods

This type of methods usually establishes optimization models for the hot rolling production planning and scheduling problem and obtains the optimal solutions by means of accurate algorithms or near-optimal solutions by heuristic algorithms. Redwine and Wismer [4] proposed an off-line iron and steel production planning and scheduling model based on the mathematical programming and found solutions to the problem through dynamic programming algorithm. Wright et al. [5] formulated a multi-objective mathematical model for scheduling the hot rolling sequences to minimize penalties as well as deviations from target delivery dates over the course of a campaign. While this model addresses both the campaign scheduling problem and turn scheduling problem, it is too large to be solved using known algorithms. For the hot strip scheduling problems in the given rolling plans, Jacobs and Wright [6] provided a goal programming model and the related algorithms. This system selects orders from order book, based upon expected revenue and inventory considerations, and places them in appropriate turns within a campaign. The system does not, however, explicitly consider the sequence in which orders within these turns are scheduled and does not explicitly consider the reduction of roller wear. Balas and Martin [7] reduced the hot rolling production scheduling problems to the knapsack constraint problems and prize collecting TSP models. For a single roll scheduling, they designed the Roll-A-Round program. Peterson et al. [8] addressed the material flow scheduling problem and time rhythm linkage from the heat furnace to the hot rolling mill (HRM) and built a multi-objective mathematical programming model and constructed effective heuristic algorithms. Kosiba et al. [9] investigated the hot strip sequencing problem and established a TSP model. However, this model only solved the single roll scheduling (turn) problem. Assaf et al. [10] addressed the steel production scheduling problem for IPSCON rolling mill and reheating furnace in Canada and developed an enumeration based optimization algorithm.

2.2. AI based methods

Hot rolling scheduling involves many practical constraints and is traditionally done by human schedulers. The quality of the schedules depends very much on the experience of the scheduler. AI based methods are considered suitable for problems with these features. The main benefits of applying AI include (1) they can handle complex constraints and generate feasible solutions, and (2) they are designed to utilize the human schedulers' experiences in the form of expert knowledge. Since these methods simulate human schedulers' decision process, the resulting schedules are easily acceptable though not optimized. AI methods used in hot rolling scheduling can be divided into (1) expert system methods and (2) constraint satisfaction methods.

2.2.1. Expert system based methods

In recent years, expert systems have found a wide range of applications in the iron and steel production scheduling. The work by Sato et al. [11] was an early attempt to solve the iron and steel production scheduling problems using expert systems. Arizono et al. [12] have developed an expert system to improve the schedules which are heuristically generated using conventional methods. Lassila et al. [13] described a knowledge-based production scheduling system built for the plate rolling mill of a large finish steel manufacture.

2.2.2. Constraint satisfaction methods

Constraint satisfaction problem (CSP) is an important branch of AI, which focuses on finding a feasible solution satisfying the constraints rather than the optimal solution. In view of the fact that the iron and steel planning and scheduling problems comprise complex constraints, it is hard to find the optimal solution to them. According to the actual demands, for most of the production scheduling problems, the constraint priority observes the following patterns: first, the rigid constraints in the production process is considered, then the related flexible constraints, and finally the optimality of the solution.

Originally, Fox [14] introduced the constraint satisfaction method into job shop scheduling problems. The production scheduling problem in the steel rolling mill was regarded as a CSP in [15]. Chang et al. [16] studied the production sequencing problems in the continuous casting-direct hot charge rolling (CC-DHCR) process, simplified the problems to a great extent, formed the Hamiltonian Loops, established the CSP model and constructed a heuristic algorithm called 'look-head'. Nevertheless, this method neglected a large number of the actual production constraints. Therefore, it was merely a methodology research and was difficult to put into practical use. Suh et al. [17] have proposed a reactive scheduling procedure based on CSP to efficiently deal with the hot-rolling reactive scheduling problem in a hot strip mill.

2.3. Human–machine coordination techniques

With this type of methods, production scheduling is carried out interactively. Although it lacks the idea of optimization, the human–machine coordination method displays the strong adaptability and flexibility for the actual complex production scheduling problems because of its easy operation and direct visualization. In recent years, the introduction of graphics and visualization technology into scheduling systems has provided more convenient interfaces for the development of the human–machine coordination technique. The Kwangyang Works of POSCO in Korea solved the rescheduling problem concerning the order change by means of human–machine coordination [18].

In Baoshan Iron & Steel Complex in China, the hot rolling scheduling system is a typical interactive system developed in Germany [19]. This system possesses the following two basic features: (1) on-line and off-line data for the production planning can be managed accurately, timely and comprehensively, and (2) based on experience and data, the scheduler can make the production plan. Afterwards, a detection link, equivalent to a tundish, is used to determine automatically whether the rigid constraints of the production process and management can be satisfied. If the plan is feasible, then the scheduling passes successfully; otherwise, the plan fails. Once the plan fails, the information violating the constraints will be pointed out and the plan will be recreated until the constraints are met.

In summary, different methods have been applied to address various scheduling problems in steel hot rolling production. AI techniques are effective in considering complex practical constraints and can simulate human schedulers' decision process. Human–machine coordination methods are flexible and can respond to changes easily. However, both methods emphasize feasibility and give inadequate consideration for optimality. Operations research based methods have the potential of optimizing the production. But the existing models only consider local optimization of one turn. In this paper, we build a global optimization model using a parallel strategy to schedule multiple turns. The model simultaneously group production orders into turns and decide the sequence for producing the orders in each turn.

3. Hot strip rolling production process and scheduling constraints

3.1. Production process

A process flow of the hot rolling mill production is shown in Fig. 1. Hot rolling orders are steel plates in rolls whose gauges range from 0.8 to 25 mm. These steel plates not only can be directly sold as finished products, but also can be further processed to form high-quality cold rolling orders. The main raw materials used in the hot strip rolling process are rough rolling plate blanks and continuous casting plate blanks. After some treatment on their surfaces, the plate blanks are heated continuously using stepping heating furnace, rolled into order blanks using rough rolling mill, refined using finish rolling mill, then cooled, rolled up and polished. The finish rolling mill set includes six or seven continuous rolling

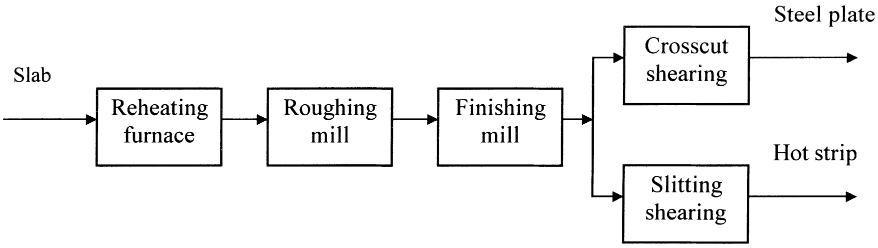

Fig. 1. Process flow of hot rolling mill production.

mill stands in the processing course. Because of the high temperature, high speed and heavy wear, work rollers and backup rollers on each stand need replacing to ensure the shape of plates and orders remaining flat. Rolling objects between two work rollers, corresponding to a rolling schedule, are called a rolling turn. Rolling objects by the whole set of rollers on the mill stand, which are made up of multiple rolling turns and correspond to multiple rolling schedules, are called a rolling set. Rolling scheduling for the hot strip rolling process is called 'hot rolling scheduling' for short.

3.2. Structure of hot rolling production operations management system

Production operational management is an important part of production management system in the steel rolling mill and production lot scheduling is the key function of production operational management, which includes the establishment of production rolling lots and the determination of production sequence in each rolling lot. Fig. 2 illustrates the overall structure of production operational management in the steel rolling mill. Within this structure the original data from the

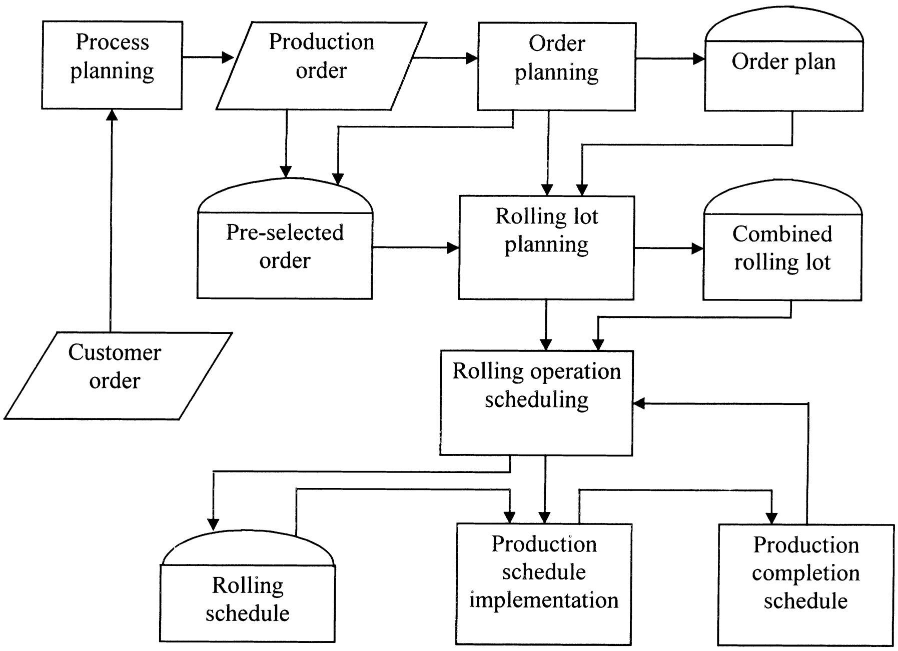

Fig. 2. Overall structure of production operational management in the steel rolling mill.

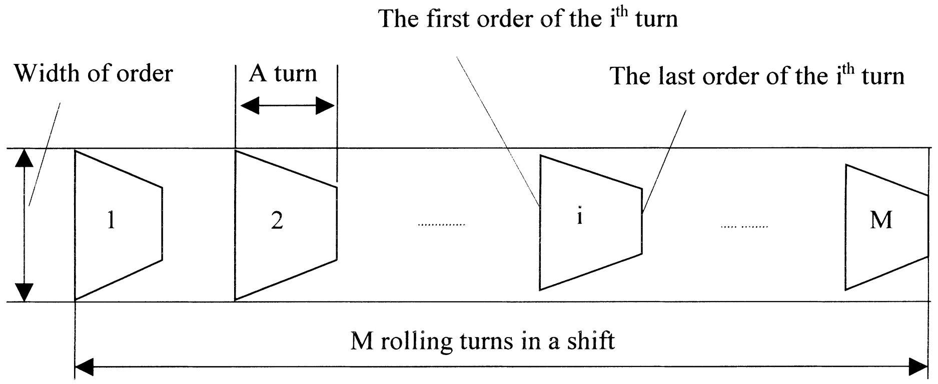

Fig. 3. The composition of a hot rolling schedule for a shift.

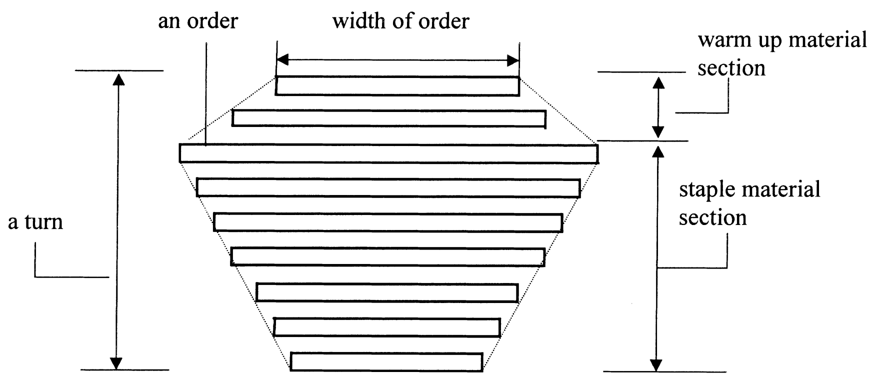

Fig. 4. The forming of a rolling turn.

customer orders are transformed into production order data through process scheduling. Pre-selected orders can be converted into reasonable order plan in terms of production capacity supply of main production processes, then a rolling lot is designed according to the process constraints and the principle of optimal cutting, and finally the rolling lot sequence is established.

3.3. Hot rolling scheduling constraints

In the hot rolling plant of Baoshan Iron & Steel Complex, every workday is divided into three shifts. Schedulers do throughput hot rolling scheduling for the next shift on the current shift. This hot rolling scheduling generally includes about 5–7 turns which are basic units of hot rolling. Fig. 3 shows the composition of a hot rolling schedule for a shift where M is the number of turns ($5 \leqslant M \leqslant 7$). The forming of a turn is shown in Fig. 4.

There are three main considerations in the hot rolling scheduling: (1) product quality; (2) roller replacement cost; and (3) roller wear. The cost of roller replacement is so great that it is necessary to organize as many orders as possible within the range of maximal rolling length constraint of a turn to reduce the replacement cost. The rolling sequence affects the roller wear. The harder the rolling orders, the greater the impact on the roller. The greater the hardness difference from order to order, the greater the impact on the roller. Gouging will result at the edge of product–roller contact area if too many orders with the same width are rolled continuously.

In order to guarantee product quality, the rolling schedules of staple materials are arranged so that each order is no wider than the one that preceded it. However, the first few orders during each turn increase in width to heat the mill, or to 'warm up' the roller as is often called. Generally, the rolling job width of a complete rolling turn appears as a 'coffin profile'. The 'warm up' material section takes on the form of outgoing coffin profile while the staple material rolling section assumes the form of inward coffin profile. The 'warm up' part is a minor part of a turn and can be easily determined by schedulers. However, the quality of the turn depends on the combination and sequence of orders in the 'staple material' part, the major part of the turn. In this paper, the term 'turn' discussed below represents the staple material section of that turn.

The staple material rolling section should meet the following requirements: (a) the total length (or weight) of the staple materials is limited to a given quantity; (b) each staple order is no wider than the one that precedes it and the width jump should be small; (c) width, gauge and hardness jumps are not permitted to occur simultaneously; (d) order gauge which is not allowed to jump repeatedly should change smoothly; (e) hardness should change gently, gradually increasing or decreasing; and (f) when changes in hardness, gauge and width compete against each other, the order of priority is: hardness, gauge and then width.

4. Characteristics and modeling strategy of hot rolling scheduling

4.1. Characteristics of hot rolling scheduling

The hot rolling scheduling problem has the following characteristics:

1. Unlike general sequencing problems, production sequencing in the steel rolling mill is affected greatly by the process constraints, which requires the specification of (a) the sequence of rolling orders and (b) the combination of rolling orders. This kind of sequencing and aggregation of products alike is referred to as sequential clustering problem.
2. Sequence-dependent setups: Different setup costs occur for changeovers between different adjacent orders.

4.2. Modeling strategies of hot rolling scheduling

As was analyzed above, hot rolling scheduling should ensure that jumps in hardness, gauge, and width are minimal.

Orders in the hot strip mill are known in advance and schedules are created only after sufficient orders have been taken. Since the setup costs or penalties are totally dependent on the physical properties of two adjacent orders, the penalties can be obtained from order to order, by direct computation. Width, gauge and hardness jumps may be quantified by a penalty structure which reflects the conditions in the hot strip mill. Now the scheduling problem becomes to sequence the orders to minimize the total penalty. The sequence with the lowest penalty will result in lower damage to the rollers, and in turn, higher product quality, hence, better profit. Penalties are only assigned from order to order and there is no penalty to sequential schedule orders of identical width, gauge and hardness. However, the gauge penalty from order to order may be asymmetrical.

Traditional hot rolling scheduling systems use a serial strategy and heavily rely on human schedulers. The turns on the same shift are arranged separately one by one. The single TSP models proposed in previous research [7,9] simulate scheduler's idea and also use the serial strategy to arrange only one turn for hot rolling scheduling. The serial strategy is essentially a greedy procedure. In the procedure a turn is arranged by selecting orders from the unscheduled order pool. The orders in the ranged turns are fixed and will not be considered further. Another turn is then scheduled by selecting orders from those remaining unscheduled. This continues until all the turns are scheduled. Clearly, with such a serial strategy, the turns arranged become poorer and poorer in terms of setup cost because the number of candidate orders in the unscheduled order pool decreases as the number of arranged turns increases. Therefore, the serial strategy suffers from the disadvantage of local optimization.

For practical hot rolling production, the orders for a shift are known in advance. It is commonly required that the schedules for M rolling turns from N orders in the pre-selected pool be worked out. Scheduling the turns sequentially is not necessary and costly. We propose a parallel strategy here to simultaneously schedule M turns for a whole shift. With this strategy, decisions are made simultaneously for grouping the N orders into M turns and sequencing the orders in each turn so as to achieve global optimization. The hot rolling scheduling problem using the parallel strategy may then be reduced to an MTSP which is the expansion of a single TSP.

5. MTSP model for rolling scheduling using the parallel strategy

5.1. The general description of MTSP

Given N cities and M salesmen, the MTSP in discussion may be stated as follows. All salesmen set out from the same fixed city and finally come back to the starting city to minimize total traveling distance. It is required that each city should be visited by exactly one salesman and each salesman should visit at least one city. The MTSP arising can be transformed to a single TSP following Lenstra and Rinnooy Kan [20].

5.2. The difference between MTSP and the hot rolling scheduling problem

As discussed in Section 4.2, the hot rolling scheduling problem may be reduced to MTSP. However, there are two aspects in which the hot rolling scheduling problem differs from the general MTSP.

(1) A feasible tour of every salesman for MTSP is a closed route. This means that for any one of the M salesmen, if he starts from point i, then he must finally returns to point i. Thus, the feasible tours of MTSP include M closed routes. However, a schedule of a turn in the actual hot rolling scheduling problem is an open path, that is, each production order is rolled exactly once. If a hot rolling schedule includes M turns then there exist only M open paths.

(2) For MTSP, all the salesmen set out from the same fixed city and finally come back to that city. However, for the hot rolling scheduling problem, starting order and ending order of each turn differ from those of other turns. This means that there are no same orders between any two turns.

5.3. Conversion of the hot rolling scheduling problem into a normal MTSP

To convert the hot rolling scheduling problem into an MTSP, we introduce M dummy nodes (orders) in two steps. First, one dummy node is introduced into the hot rolling scheduling problem and let all turns start from and end at this dummy node. This dummy node acts as both source node and destination node to make closed routes. Then $M-1$ additional dummy nodes (order) are introduced to ensure that M closed routes are made and every node should be visited by exactly one salesman, e.g., each production order is rolled exactly once.

5.4. MTSP model for the hot rolling scheduling problem

Assume that N orders are to be rolled in M rolling turns on one shift. These N orders may be viewed as N nodes and M turns may be regarded as the tours by M traveling salesmen. By adding M dummy nodes, $N+1, N+2, \ldots, N+M$, the rolling scheduling problem can be viewed as an MTSP as discussed above. The problem can then be reduced to a single TSP, that is, one traveling salesman visits $N+M$ cities.

We define the following variables and parameters:

$$X_{ij} = \begin{cases} 1 & \text{if order } j \text{ immediately follows order } i \\ & \text{in the same turn,} \\ 0 & \text{otherwise,} \end{cases}$$
$$\text{for } i, j \in \{1, \ldots, N\},\ i \neq j,$$

$$X_{ij} = \begin{cases} 1 & \text{if order } j \text{ is the first to be produced} \\ & \text{in turn } i - N, \\ 0 & \text{otherwise,} \end{cases}$$
$$\text{for } i \in \{N+1, \ldots, N+M\},$$
$$j \in \{1, \ldots, N\},$$

$$X_{ij} = \begin{cases} 1 & \text{if order } i \text{ is the last to be produced} \\ & \text{in turn } j - N, \\ 0 & \text{otherwise,} \end{cases}$$
$$\text{for } i \in \{1, \ldots, N\},$$
$$j \in \{N+1, \ldots, N+M\}.$$

$C_{ij} =$ penalty cost for production changeover from order i directly to order j.

These cost parameters are further defined below in detail for different orders (real or dummy) involved.

$$C_{ij} = P^{\mathrm{w}}_{ij} + P^{\mathrm{g}}_{ij} + P^{\mathrm{h}}_{ij}, \quad i, j \in \{1, \ldots, N\}, \quad i \neq j, \tag{1}$$

where P^{w}_{ij}, P^{g}_{ij}, and P^{h}_{ij} represent penalty for width, gauge and hardness jumps from order to order, respectively.

$$C_{ij} = 0, \qquad i \in \{1, \ldots, N\}, \quad j \in \{N+1, \ldots, N+M\}, \tag{2}$$

$$C_{ij} = 0, \qquad i \in \{N+1, \ldots, N+M\}, \quad j \in \{1, \ldots, N\}, \tag{3}$$

$$C_{ij} = \infty, \qquad i, j \in \{N+1, \ldots, N+M\}, \tag{4}$$

$$C_{ii} = \infty, \qquad i \in \{1, \ldots, N+M\}. \tag{5}$$

The mathematical model can then be formulated as follows:

(P)

$$\text{minimize} \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} C_{ij} X_{ij}, \tag{6}$$

subject to

$$\sum_{i=1}^{N+M} X_{ij} = 1, \quad j \in \{1, 2, \ldots, N+M\}, \tag{7}$$

$$\sum_{j=1}^{N+M} X_{ij} = 1, \quad i \in \{1, 2, \ldots, N+M\}, \tag{8}$$

$$\sum_{i \in S} \sum_{j \in S \setminus \{i\}} X_{ij} \leqslant |S| - 1, \quad S \subset \{1, \ldots, N+M\}, \quad 2 \leqslant |S| \leqslant N+M-2, \tag{9}$$

$$X_{ij} \in \{0, 1\}, \quad i, j \in \{1, \ldots, N+M\}. \tag{10}$$

The solution of this model will give a complete schedule consisting of M turns, each starting from a dummy order. The complete schedule corresponds to a optimal tour in the TSP. In the model the objective function (6) is to minimize the total changeover costs. Constraints (7) ensure that exactly one task is rolled before order j. Constraints (8) guarantee that exactly one order is rolled after order i. Constraints (9) avoid subschedules (corresponding to subtours for TSP) in the feasible solutions. Constraints (10) requires that the variables only take integer values of 0 or 1. Note that, with constraints (7) and (8), subschedules over one order cannot occur. Therefore subschedules over $N + M - 1$ orders cannot occur either (otherwise a subschedule would occur over the remaining one order). Thus, it is valid to define constraints (9) for $2 \leqslant |S| \leqslant N + M - 2$ only. It is essential to avoid subschedules to ensure a complete schedule in the solution. Fig. 5 shows two subschedules for an example problem with six orders. Without constraints (9), the subschedules would be a feasible solution. However, they do not satisfy (9) and therefore are not feasible for (P). For further

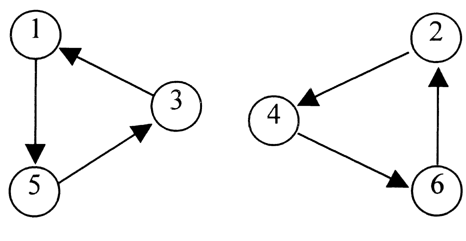

Fig. 5. Two subschedules for a problem with six orders.

information on this type of constraints in the TSP context, please refer to [21,22].

6. A modified genetic algorithm (MGA) for solving TSP

6.1. General genetic algorithm for TSP

GAs are adaptive searching procedures for solving optimization problems based on the mechanics of natural genetics and natural selection. Goldberg [23] and Grefenstette et al. [24] first applied GAs to solve TSP. A general GA for TSP may be described as follows. The procedure starts from a group of initial solutions called the initial population. Each solution (a tour) is represented by a sequence of all the cities, in which the tour is formed. The sequence for a solution is often called a chromosome following the term used in genetics. A fitness function is used to evaluate the performance of the solutions. The shorter the tour distance, the higher the fitness value. Each time two solutions, called parent solutions, are chosen from the population according to the selection probability which is proportional to their fitness value. The two parent solutions then crossover to produce one or two new solutions of the next generation. A mutation operation (changing the sequence of cities in the tour) is then applied to the newly generated solutions based on a mutation probability. Repeat these operations (selection, crossover, and mutation) to produce more new solutions until the population size of the new generation is the same as that of the old one. The iteration then starts from the new population. Since better solutions have a larger probability to be selected for crossover and the new solutions produced carries the features of their parents, it is hoped that the new generation will be better than the old one. The procedure continues until a preset maximum number of generations is reached or the solution quality cannot be easily improved.

The crossover operation combines features of the two parent solutions and passes them to the child solutions by exchanging part of their sequences. Since direct exchange of corresponding cities in the two tours may result in infeasible solutions (some cities are visited more than once while some others are not visited), the crossover operators for TSP are specially designed to be capable of repairing the child chromosomes to guarantee feasibility. Three crossover operators have been proposed in the literature. They are partially matched crossover (PMX), order crossover (OX) and cycle crossover (CX) [25]. PMX and OX are different kinds of crossover processes although they bear much similarity. Much attention is paid to absolute city positions in the PMX process, while much emphasis is placed on relative city positions in the OX process. CX differs considerably from PMX and OX in that each city is obtained by a combination of the cities from parent cities.

While these crossover operators ensure feasibility by repairing the child chromosomes, the repair also destroys the features of parent chromosomes, the good segment of genes in the parent chromosomes may not be inherited. In addition, because the parent chromosomes are selected randomly, there is no guarantee that the best solutions are selected though the probability for their selection is higher. As a result the convergence of the general GA for TSP is slow.

6.2. The modified genetic algorithm (MGA)

When using GA to solve an optimization problem, we want it to converge quickly. On the other hand, we do not want to see pre-mature convergence (trapped in local optimum). It is often difficult for the general GA procedure to keep a good balance between the two (computation time and solution quality). We propose a MGA for the TSP for a better trade-off between the two conflicting criteria. In the MGA, a new way of selecting parent solutions for the crossover operation is suggested and used. For the crossover operations in the MGA, we always choose the best solution appeared so far to be one of the parent chromosomes in every crossover operation. The other parent chromosome is selected in the same way as in the general GA. The actual crossover is

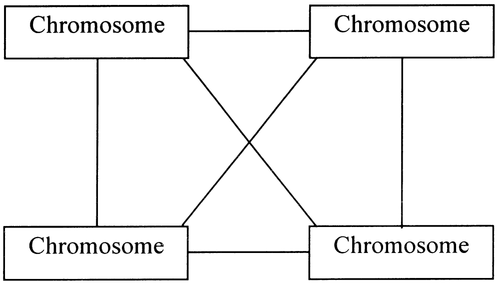

Fig. 6. Crossover framework of the general GA.

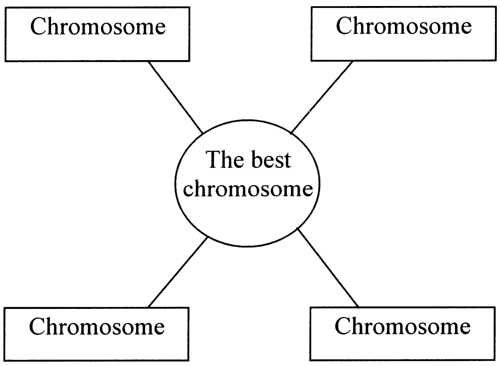

Fig. 7. Crossover framework of the MGA.

still done using CX. We call the crossover operation using parents selected this way 'seed based crossover'.

The frameworks of the general GA and the MGA are illustrated in Figs. 6 and 7, respectively.

In the MGA, the initial population can be generated randomly. Some of the solutions in the initial population may also be generated using constructive heuristics such as the nearest neighbor heuristic. The best solution in the initial population is then selected as the seed for the first generation. After each generation, the best solution of the new population will be compared with the current seed, the better one will be selected as the new seed. Since in this way the best solution is always selected, there is a greater chance for the best features to be passed on to the next generation. The random selection of the other parent solution brings diversity to the next generation and therefore prevents premature convergence. Therefore the MGA will be more effective.

6.3. Computational experiment

We have implemented the MGA for solving the TSP model of the hot rolling scheduling problem based on the structure described above. In this MGA, the representation of solutions, fitness function, and mutation operation are all chosen in the same way as in the GA of [23]. The parameters are set as follows:
maximum number of generations = 6000,
population size = 100,
probability of crossover = 0.99,
probability of mutation = 0.01.

To evaluate the performances of the MGA, computational experiment has been carried out on 50 randomly generated problem instances. The number of orders for these problem instances was chosen at five levels: 50, 75,100, 125, and 150. Each level corresponds to one problem instance set which includes 10 problem instances. The changeover costs between any two orders were randomly generated from uniform distributions of which range was set to be from 1 to 500 for all problem instances.

Volgenant and Jonker's [26] exact algorithm were used for comparison. Two criteria are used for the comparison and evaluation – optimality and computation time. We use a ratio of C/C^* as optimality measurement, where C^* is the objective value of the optimal solution for the problem instance and C is the objective value for the same instance given by the MGA. The average optimality performances and computational time are shown in Table 1.

From the figures in Table 1, we can see that:

1. MGA is very close to the exact algorithm in optimality performance. The average deviation of MGA solution from the optimal solution is about 5%.
2. The computation time of both MGA and exact algorithm increases when the problem size increases. All the times shown are in seconds on a Pentium PC. However, the increase rate for computational effort of MGA is less than that

Table 1
The optimality performance and computational time of MGA for TSP

Number of cities	Optimality performance		Computational time (s)	
	Volgenant & Jonker's exact algorithm	MGA	Volgenant & Jonker's exact algorithm	MGA
50	1.0000	1.0272	72	159
75	1.0000	1.0343	76	263
100	1.0000	1.0613	183	396
125	1.0000	1.0639	406	559
150	1.0000	1.0727	886	745

of the exact algorithm. Hence the MGA may be applied to larger problems.

7. Implementation and practical application of the scheduling system

7.1. Applications of the MTSP model and the MGA in the hot rolling scheduling

To demonstrate application of the MTSP model and the MGA, they have been employed to recreate hot strip rolling schedules using production data in Shanghai Baoshan Iron & Steel Complex. The scheduling objective is to minimize the total penalty cost. A typical structure for width, hardness and gauge changeover cost which is proposed by Kosiba et al. [9] is shown in Tables 2–4, respectively. P_{ij}^{w}, P_{ij}^{g} and P_{ij}^{h} represent penalties for width, gauge and hardness jumps between adjacent orders, respectively. We have taken this typical structure as penalty cost in the hot rolling system we implemented.

Table 2
Width penalty structure (P_{ij}^{w})

Inward jump (cm)	Penalty (points)
0–3	1
3–6	2
6–9	3
9–12	5
12–15	10
15–18	20
18–21	30
21–24	50
24–27	70
27–30	90
30–33	120
33–36	150
36–54	200
54–90	500
90–150	1000

Table 3
Hardness penalty structure (P_{ij}^{g})

Factor change	Penalty (points)
1	5
2	15
3	35
4	60
5	75

Table 4
Gauge penalty structure (P_{ij}^{h})

Excess jump (cm)	Penalty (points for jump up/down)	
0.0003–0.03	3	6
0.0303–0.06	7	14
0.0601–0.09	12	24
0.0901–0.12	18	36
0.1201–0.15	25	50
0.1501–0.18	33	66
0.1801–0.21	42	84
0.2101–0.24	52	104
0.2401–0.30	66	132
0.3010–0.45	99	198
0.4501–3.00	199	398

Tables 5 and 6 show the actual rolling sequences made by manual agent and by MTSP/MGA respectively for orders of one shift. It is clear that the total penalty of the solution by MTSP/MGA is far less than that by manual sequencing. This result demonstrates that a hot rolling schedule produced using the proposed

Table 5
Actual hot rolling sequence created by manual scheduling[a,b]

Seq. No.	Order No.	Rolling			Seq. No.	Order No.	Rolling		
		Width	Gauge	Hard-ness			Width	Gauge	Hard-ness
1	RE31081900	1530	5.88	3	35	RE3025300	1250	4.03	5
2	RE31083200	1530	5.89	3	36	RE3025300	1250	4.03	3
3	RE31700400	1530	4.97	5	37	RE3025300	1250	4.03	3
4	RE31700400	1530	4.97	5	38	RE3025300	1250	4.02	3
5	RE31700400	1530	4.97	5	39	RE3025300	1250	4.02	3
6	RE31505700	1530	4.97	4	40	RE30219300	1230	4.02	2
7	RE35702201	1500	5.89	4	41	RE3025300	1230	4.02	2
8	RE35702201	1500	5.89	4	42	RE3025300	1230	4.02	2
9	RE35702201	1500	5.89	4	43	RE3025300	1230	4.02	2
10	RE35702201	1500	5.89	4	44	RE3025302	1150	4.03	2
11	RE35702201	1500	5.89	4	45	RE3025302	1150	4.03	2
12	RE35702201	1500	5.89	4	46	RE30181800	1200	4.02	2
13	RE35702201	1500	5.89	4	47	RE30181800	1200	4.02	2
14	RE35702201	1500	5.89	4	48	RE30180812	1150	4.03	4
15	RE35702201	1500	5.89	4	49	RE30180812	1150	4.03	4
16	RE35702201	1500	5.89	4	50	RE30180812	1150	4.03	4
17	RE35702201	1500	5.89	4	51	RE30181800	1150	4.02	4
18	RE35702201	1500	5.89	4	52	RE30252600	1050	4.01	4
19	RE35702201	1500	5.89	4	53	RE30252600	1050	4.01	4
20	RE35702201	1500	5.89	4	54	RE30354600	1030	4.05	3
21	RE35702201	1500	5.89	4	55	RE30354600	1030	4.04	3
22	RE35702201	1500	5.89	4	56	RE30354600	1030	4.04	3
23	RE35702201	1500	5.89	4	57	RE30354600	1030	4.04	3
24	RE35702201	1530	5.89	4	58	RE30354600	1030	4.03	3
25	RE35702201	1500	5.89	4	59	RE3354700	1020	3.53	2
26	RE35702201	1500	5.89	4	60	RE3354700	1020	3.53	2
27	RE35702201	1500	5.89	4	61	RE3214700	1020	3.14	2
28	RE30240200	1500	5.89	4	62	RE3214700	1020	3.14	2
29	RE30240200	1500	4.96	4	63	RE3214700	1020	3.14	2
30	RE30183600	1280	4.96	5	64	RE3214700	1020	3.12	2
31	RE30724002	1280	4.93	5	65	RE32801800	1000	3.25	1
32	RE30181800	1280	4.97	5	66	RE32801800	1000	3.25	1
33	RE30181800	1280	4.97	5	67	RE32801800	1000	3.25	1
34	RE31081800	1280	4.97	5	68	RE32801800	1000	3.25	1

[a] Penalty coefficients are shown in Tables 2–4, respectively.
[b] Objective value = 368.

MTSP/MGA is superior to one created from the manual experience. In this experiment the total penalty of the schedule generated by the MTSP/MGA method has decreased by 25.5335% compared with the result of manual scheduling.

7.2. Implementing and running of a hot rolling scheduling system

As the practical running results show, the proposed scheduling method can reduce human schedulers' burden and improve productivity significantly. The schedulers consider it a very useful tool. However, they indicate that the GA evaluation function should be easily changed on-screen because the operational constraints vary daily. To make the scheduling system compatible with field requirements, we combined the MTSP model and MGA with man–machine interactive methods. A hot rolling scheduling system has been developed using C++, and SYBASE database and implemented in Baoshan Iron & Steel Complex at the end of 1997. Major steps of using the system to

Table 6
Hot rolling sequence generated by MTSP/MGA[a,b]

Seq. No.	Order No.	Rolling			Seq. No.	Order No.	Rolling		
		Width	Gauge	Hardness			Width	Gauge	Hardness
1	RE31081900	1530	5.88	3	35	RE3025300	1250	4.03	5
2	RE31083200	1530	5.89	3	36	RE3025300	1250	4.03	3
6	RE31505700	1530	4.97	4	38	RE3025300	1250	4.03	3
5	RE31081900	1530	5.88	3	39	RE3025300	1250	4.02	3
4	RE31700400	1530	4.97	5	37	RE3025300	1250	4.02	3
3	RE31700400	1530	4.97	5	42	RE3025300	1230	4.02	2
29	RE30240200	1500	4.96	4	40	RE30219300	1230	4.02	2
26	RE35702201	1500	5.89	4	41	RE3025300	1230	4.02	2
10	RE35702201	1500	5.89	4	43	RE3025300	1230	4.02	2
16	RE35702201	1500	5.89	4	46	RE30181800	1200	4.02	2
28	RE35702201	1500	5.89	4	47	RE30181800	1200	4.02	2
17	RE35702201	1500	5.89	4	49	RE30180812	1150	4.03	4
22	RE35702201	1500	5.89	4	51	RE30181800	1150	4.02	4
24	RE35702201	1500	5.89	4	45	RE3025302	1150	4.03	2
25	RE35702201	1500	5.89	4	44	RE3025302	1150	4.03	2
11	RE35702201	1500	5.89	4	50	RE3025302	1150	4.03	2
21	RE35702201	1500	5.89	4	48	RE30180812	1150	4.03	4
20	RE35702201	1500	5.89	4	53	RE30252600	1050	4.01	4
18	RE35702201	1500	5.89	4	52	RE30252600	1050	4.01	4
19	RE35702201	1500	5.89	4	56	RE30354600	1030	4.03	3
12	RE35702201	1500	5.89	4	54	RE30354600	1030	4.04	3
23	RE35702201	1500	5.89	4	57	RE30354600	1030	4.04	3
23	RE35702201	1500	5.89	4	55	RE30354600	1030	4.04	3
27	RE35702201	1530	5.89	4	58	RE30354600	1030	4.05	3
9	RE35702201	1500	5.89	4	59	RE3354700	1020	3.53	2
8	RE35702201	1500	5.89	4	60	RE3354700	1020	3.53	2
14	RE35702201	1500	5.89	4	61	RE3214700	1020	3.14	2
13	RE35702201	1530	5.89	4	64	RE3214700	1020	3.14	2
15	RE35702201	1500	5.89	4	62	RE3214700	1020	3.14	2
32	RE30181800	1280	4.97	5	63	RE3214700	1020	3.12	2
34	RE31081800	1280	4.97	5	68	RE32801800	1000	3.25	1
33	RE30181800	1280	4.97	5	67	RE32801800	1000	3.25	1
30	RE30183600	1280	4.96	5	65	RE32801800	1000	3.25	1
31	RE30724002	1280	4.93	5	66	RE32801800	1000	3.25	1

[a] Penalty coefficients are shown in Tables 2–4, respectively.
[b] Objective value = 274.

find solutions to hot rolling scheduling problems are given as follows.

Step 1: Generate reference solutions called initial solutions using the MGA based on the MTSP model presented in Section 5.

Step 2: Show these initial solutions using charts and tables. The first frame shows the overview charts of all turns in the shift to be scheduled. According to the information of the overview charts, scheduler can go into any other frames showing subcharts by selecting the 'enter chart' command. A subchart shows the composition of a turn as presented in Section 3.3. The information of that turn is detailed in tables by selecting the 'enter table' command.

Step 3: Operate the edit function of the scheduling system. With this function, the initial solutions can be adjusted to produce modified solutions using man–machine interactive method. The scheduler can judge the quality of the initial solutions by checking frames and tables in step 2. If the initial solutions are not satisfactory, the scheduler can modify the initial solutions by selecting the modification command. There are two kinds of modification modes. One is to change an order sequence within a turn and the other is to move an order from one turn to another. This step needs to be repeated until the schedule is satisfactory.

Step 4: Check the feasibility of the modified solutions. There are 12 rules in the system to determine whether the modified solutions are feasible. These rules include some hard constraints taken from the production practice. The solutions are regarded as feasible only if all these rules are satisfactory. For infeasible solutions, the system will indicate which rules are not satisfactory. If the solutions are feasible, go to step 5. Otherwise go to step 3.

Step 5: Obtain and output the final solutions. Repeat steps 3 and 4 if necessary.

This system has been used successfully for one year and has demonstrated two benefits. (1) It improves hot rolling scheduling quality. Hot rolling schedules created by the new system are superior to that produced by the manual system. The average improvement by the new system is over 20% in comparison with the old system (manual system). (2) It reduces the time for creating the hot rolling schedules. The new scheduling system takes about 40 minutes to produce the final schedule, while the old system takes about 4 hours.

8. Conclusions

Iron and steel industry is essential for rapidly developing economies and often serves as a driving force for their industrial development. The industry is also capital and energy intensive and therefore effective production scheduling is very important.

In this paper we studied the hot rolling scheduling problem in iron and steel plants and proposed a parallel strategy to simultaneously schedule multiple turns in the same shift. This new strategy seeks global optimization for the whole shift and therefore is superior to the traditional serial strategy which considers only local optimization for each turn. Using the proposed parallel strategy a MTSP model was built for the problem based on actual production constraints. A MGA was constructed to obtain a near-optimal solution to the model. Combining the proposed MTSP model and the MGA with man–machine interactive method, a practical hot rolling scheduling system has been developed and implemented in Shanghai Baoshan Iron & Steel Complex, China. One year's application of the system has shown 20% improvement over the previous manual based system.

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